Large Scale Landuse Classification of Satellite Imagery

Suneel Marthi
Jose Luis Contreras

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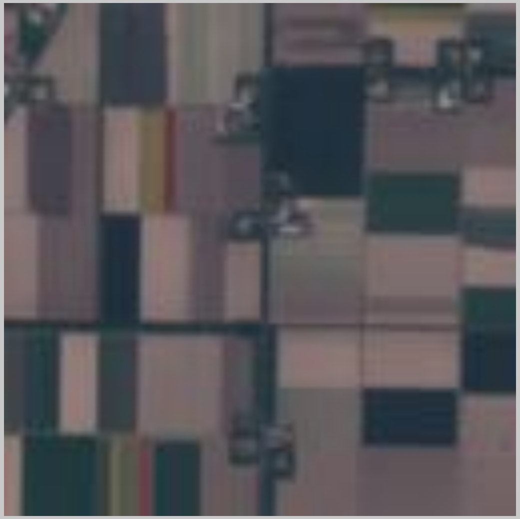
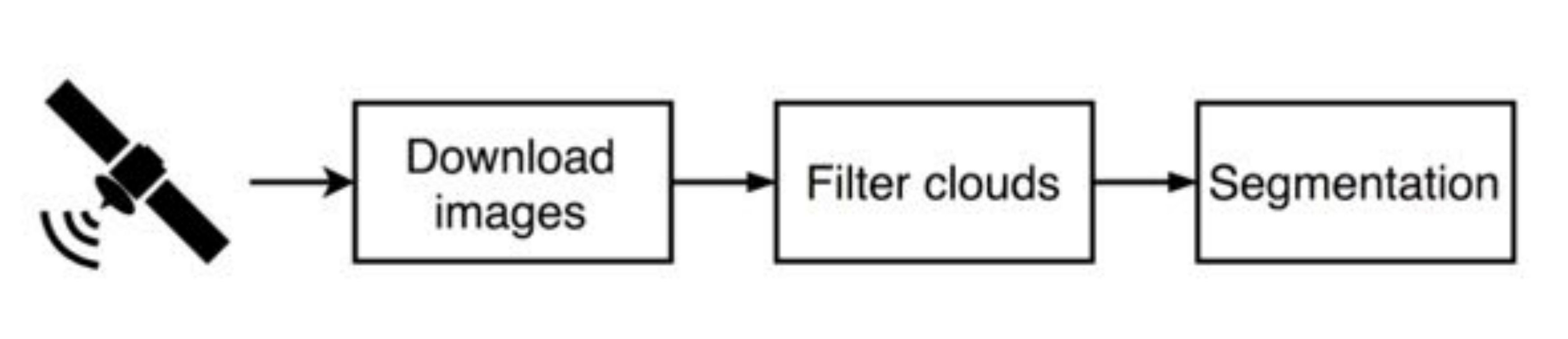
Agenda

- Introduction
- Satellite Image Data Description
- Cloud Classification
- Segmentation
- Apache Beam
- Beam Inference Pipeline
- Demo
- Future Work

Goal: Identify Tulip fields from Sentinel-2 satellite images



Workflow



Data: Sentinel-2

Earth observation mission from ESA

13 spectral bands, from RGB to SWIR (Short Wave Infrared)

Spatial resolution: 10m/px (RGB bands)

5 day revisit time

Free and open data policy

Data acquisition

Images downloaded using Sentinel Hub’s WMS (web mapping service)

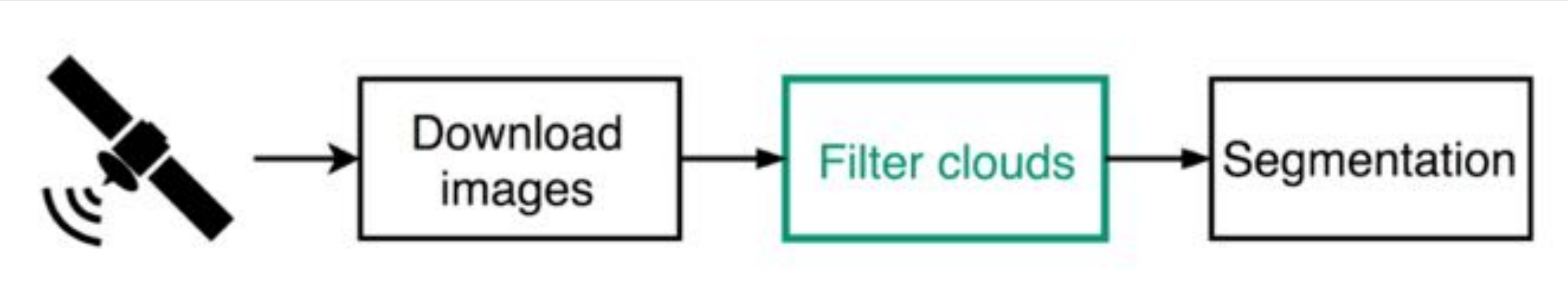
Download tool from Matthieu Guillaumin (@mguillau)

SENTINEL Hub by SINERGISE

Data

256 x 256 px images, RGB

Workflow



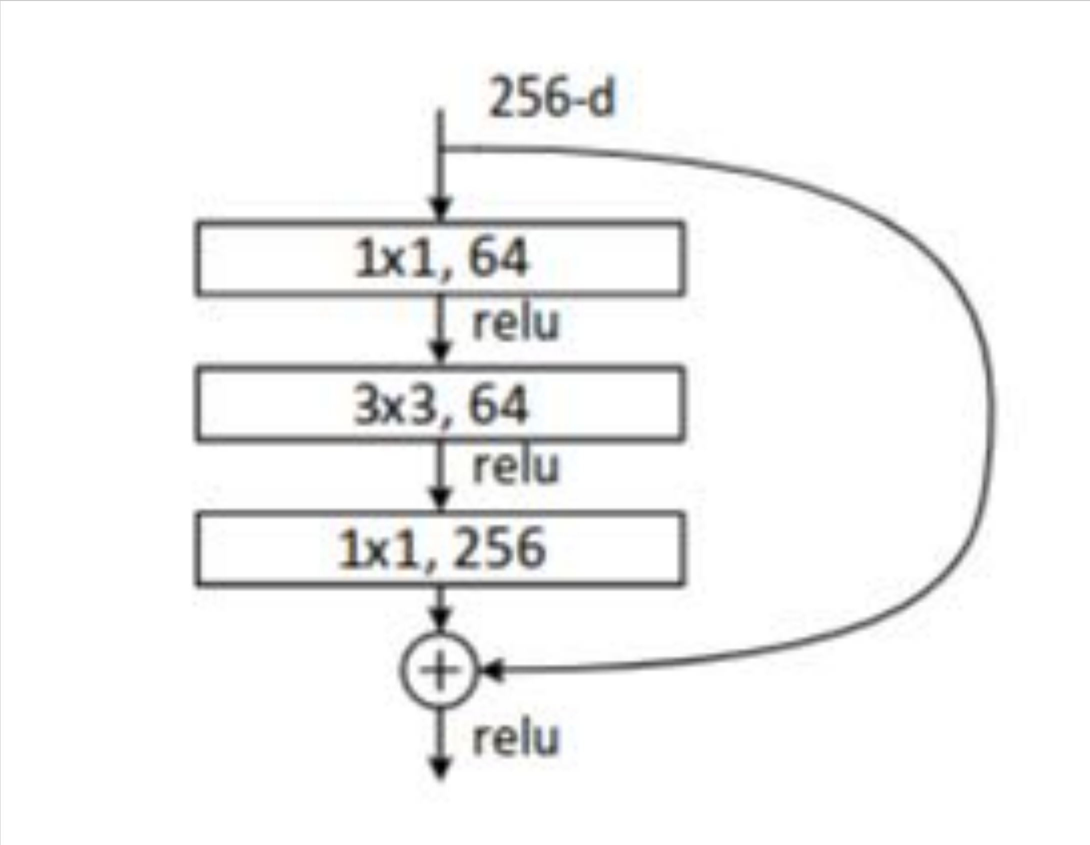
Filter Clouds

Need to remove cloudy images before segmenting

Approach: train a Neural Network to classify images as clear or cloudy

CNN Architectures: ResNet50 and ResNet101

ResNet building block



Filter Clouds: training data

‘Planet: Understanding the Amazon from Space’ Kaggle competition

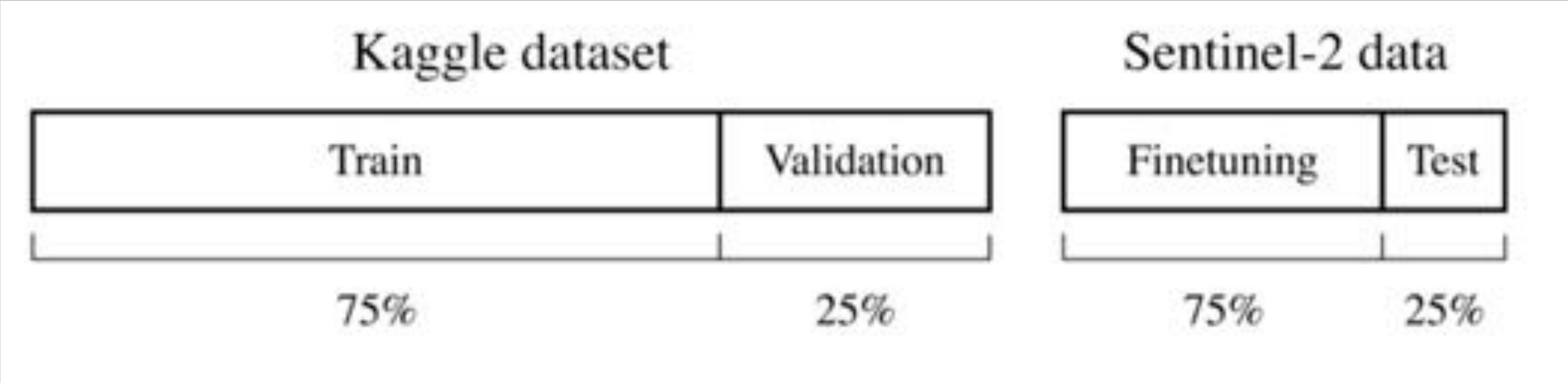
40K images labeled as clear, hazy, partly cloudy or cloudy

Filter Clouds: Training data(2)

Origin	No. of Images	Cloudy Images
Kaggle Competition	40000	30%
Sentinel-2(hand labelled)	5000	50%
Total	45000	32%

Only two classes: clear and cloudy (cloudy = haze + partly cloudy + cloudy)

Training data split

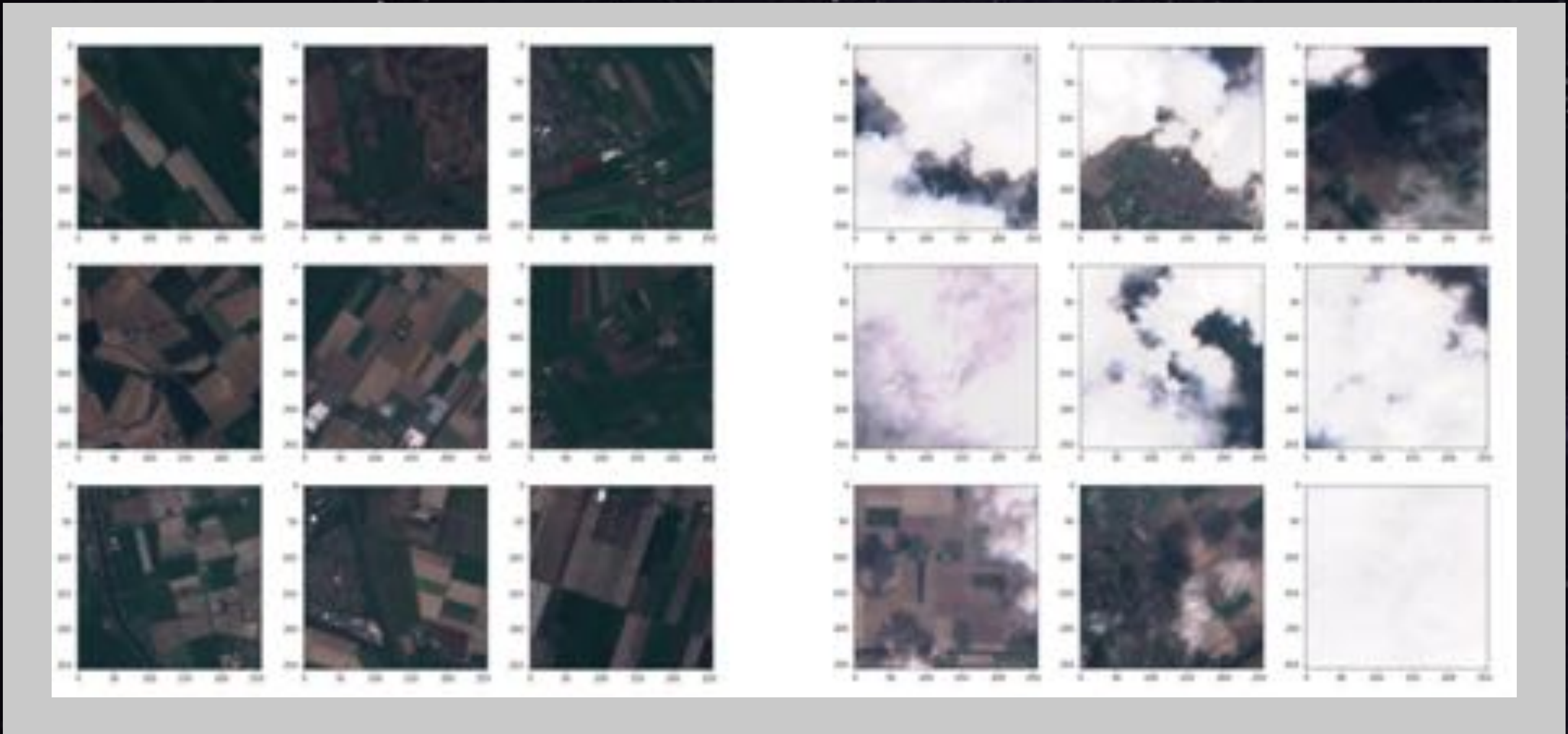


Results

Model	Accuracy	F1	Epochs (train + finetune)
ResNet50	0.983	0.986	23 + 7
ResNet101	0.978	0.982	43 + 9

Choose ResNet50 for filtering cloudy images

Example Results

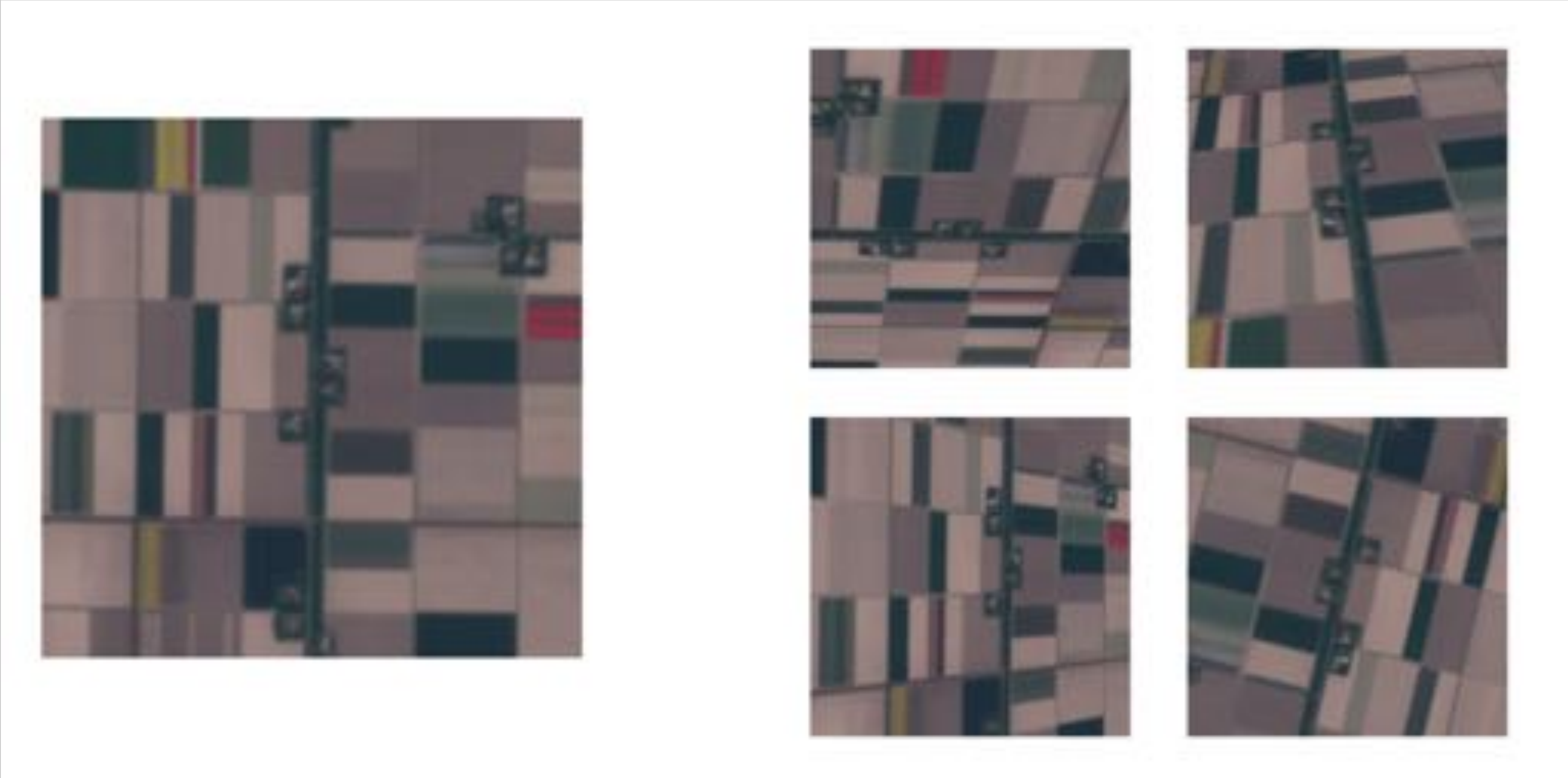


Data Augmentation

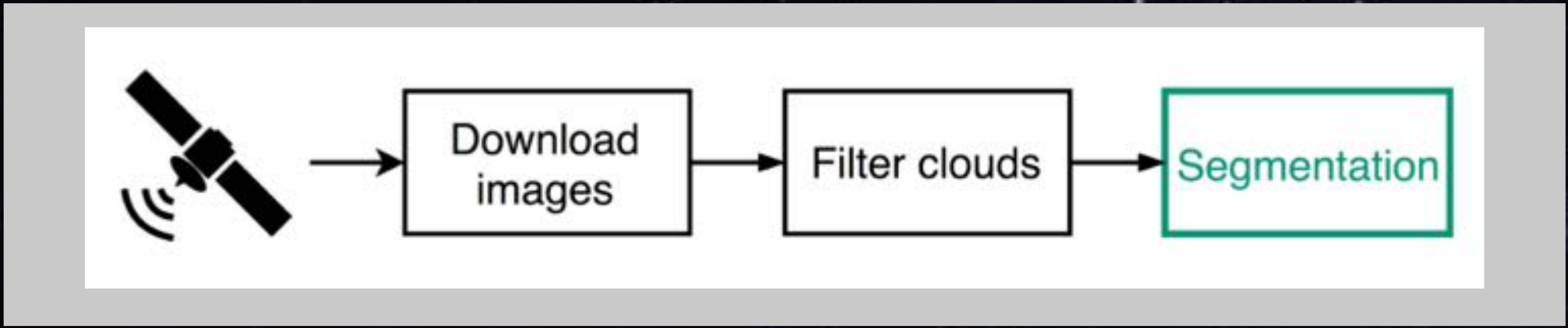
Augmentor

```
import Augmentor

p = Augmentor.Pipeline(img_dir)

p.skew(probability=0.5, magnitude=0.5)
p.shear(probability=0.3, max_shear=15)
p.flip_left_right(probability=0.5)
p.flip_top_bottom(probability=0.5)
p.rotate_random_90(probability=0.75)
p.rotate(probability=0.75, max_rotation=20)
```

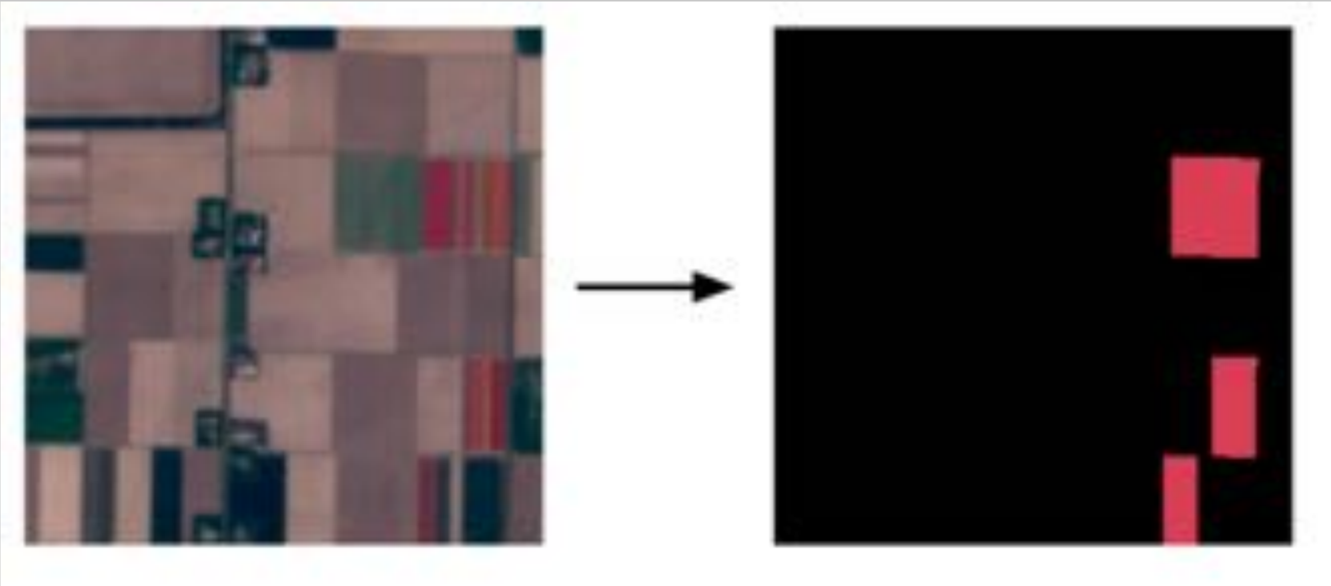
Example Data Augmentation



Workflow



Segmentation Goals

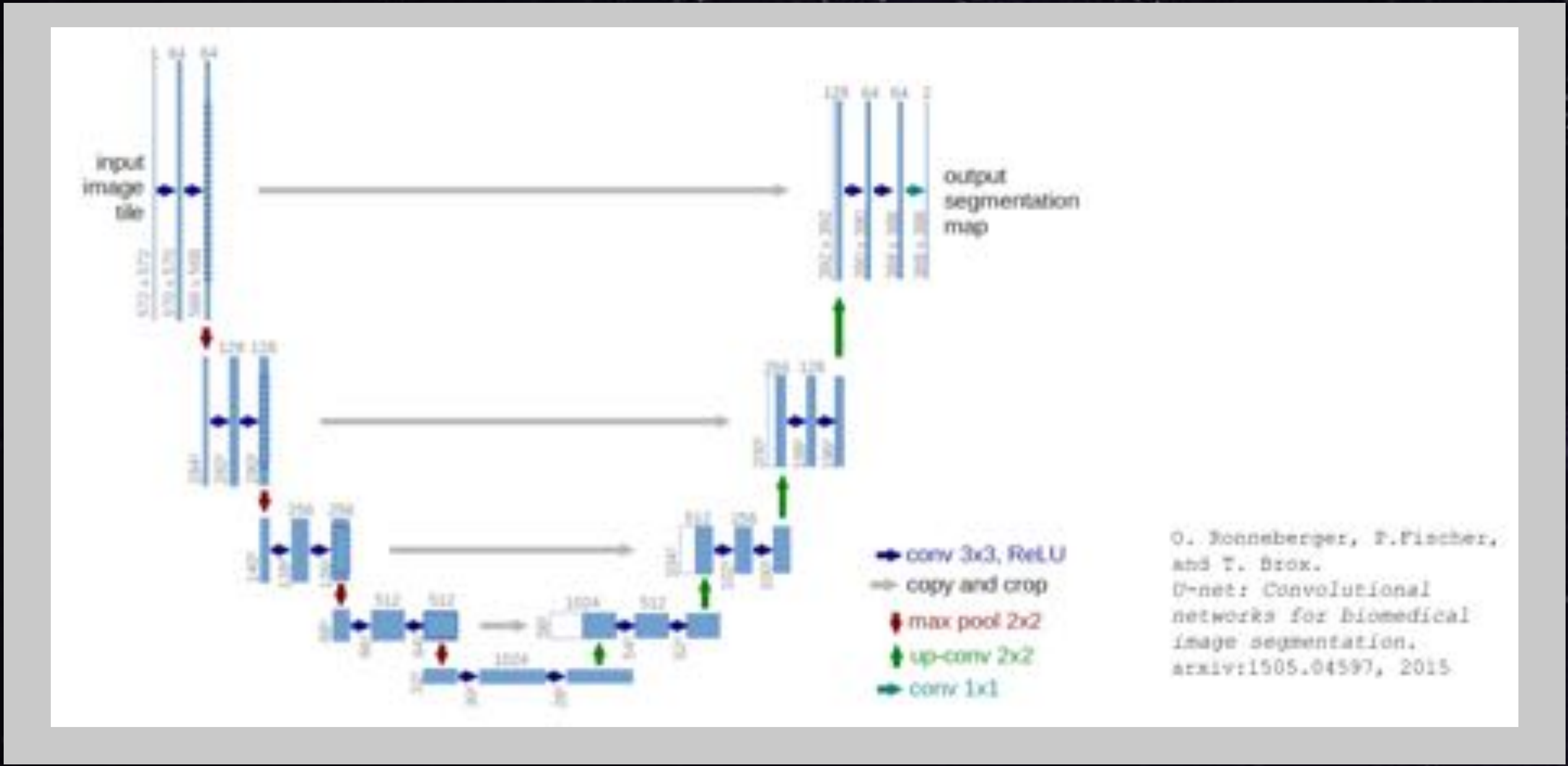


Approach U-Net

- State of the Art CNN for Image Segmentation
- Commonly used with biomedical images
- Best Architecture for tasks like this

O. Ronneberger, P.Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. arxiv:1505.04597, 2015

U-Net Architecture



U-Net Building Blocks

```
def conv_block(channels, kernel_size):
    out = nn.HybridSequential()
    out.add(
        nn.Conv2D(channels, kernel_size, padding=1, use_bias=False
        nn.BatchNorm(),
        nn.Activation('relu')
    )
    return out
```

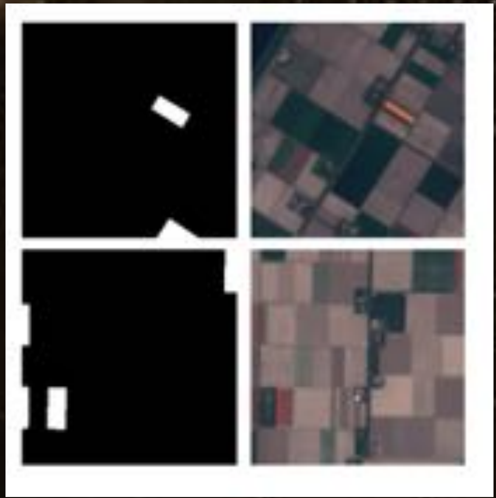
```
def down_block(channels):
    out = nn.HybridSequential()
    out.add(
        conv_block(channels, 3),
        conv_block(channels, 3)
    )
    return out
```

U-Net Building Blocks (2)

```
class up_block(nn.HybridBlock):
    def __init__(self, channels, shrink=True, **kwargs):
        super(up_block, self).__init__(**kwargs)
        self.upsampler = nn.Conv2DTranspose(channels=channels, ker
                                            strides=2, padding=1,
        self.conv1 = conv_block(channels, 1)
        self.conv3_0 = conv_block(channels, 3)
        if shrink:
            self.conv3_1 = conv_block(int(channels/2), 3)
        else:
            self.conv3_1 = conv_block(channels, 3)
    def hybrid_forward(self, F, x, s):
        x = self.upsampler(x)
        x = self.conv1(x)
        x = F.relu(x)
        x = F.Crop(*[x,s], center_crop=True)
```

U-Net: Training data

- Ground truth: tulip fields in the Netherlands
- Provided by Geopedia, from Sinergise



Loss function: Soft Dice Coefficient loss

$$Dice = -2 \cdot \frac{|prediction \cap label|}{|prediction| + |label| + \varepsilon}$$

Prediction = Probability of each pixel belonging to a Tulip Field (Softmax output)

ε serves to prevent division by zero

Evaluation Metric: Intersection Over Union(IoU)

$$IoU = \frac{|prediction \cap label|}{|prediction \cup label| + \varepsilon}$$

Aka Jaccard Index

Similar to Dice coefficient, standard metric for image segmentation

Results

- **IoU = 0.73** after 23 training epochs
- Related results: DSTL Kaggle competition
- IoU = 0.84 on crop vs building/road/water/etc segmentation

https://www.kaggle.com/c/dstl-satellite-imagery-feature-detection/discussion/29790

Was ist Apache Beam?

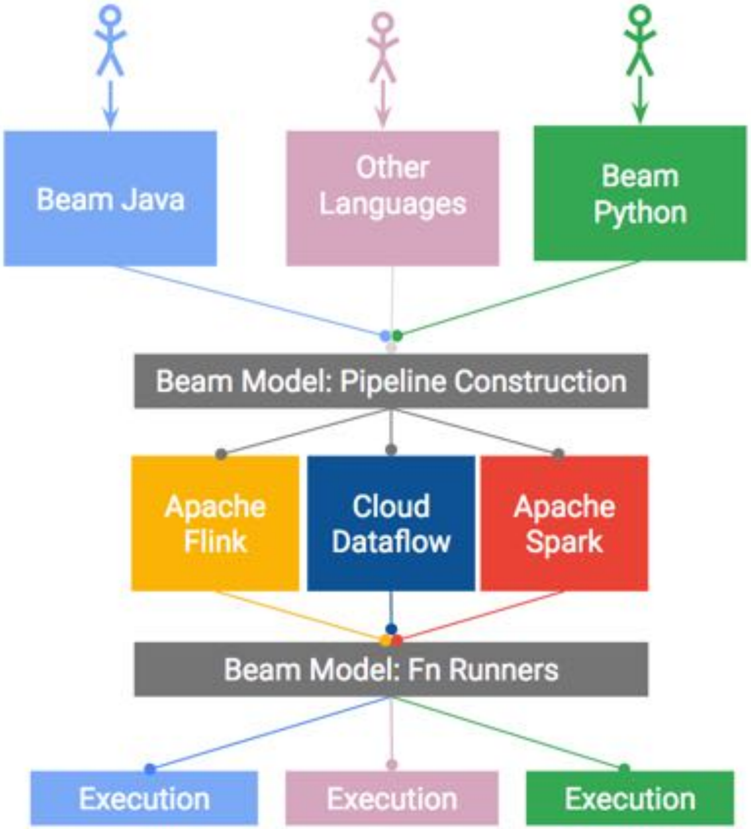
- Agnostic (unified Batch + Stream) programming model
- Java, Python, Go SDKs
- Runners for Dataflow
  - Apache Flink
  - Apache Spark
  - Google Cloud Dataflow
  - Local DataRunner

Warum Apache Beam?

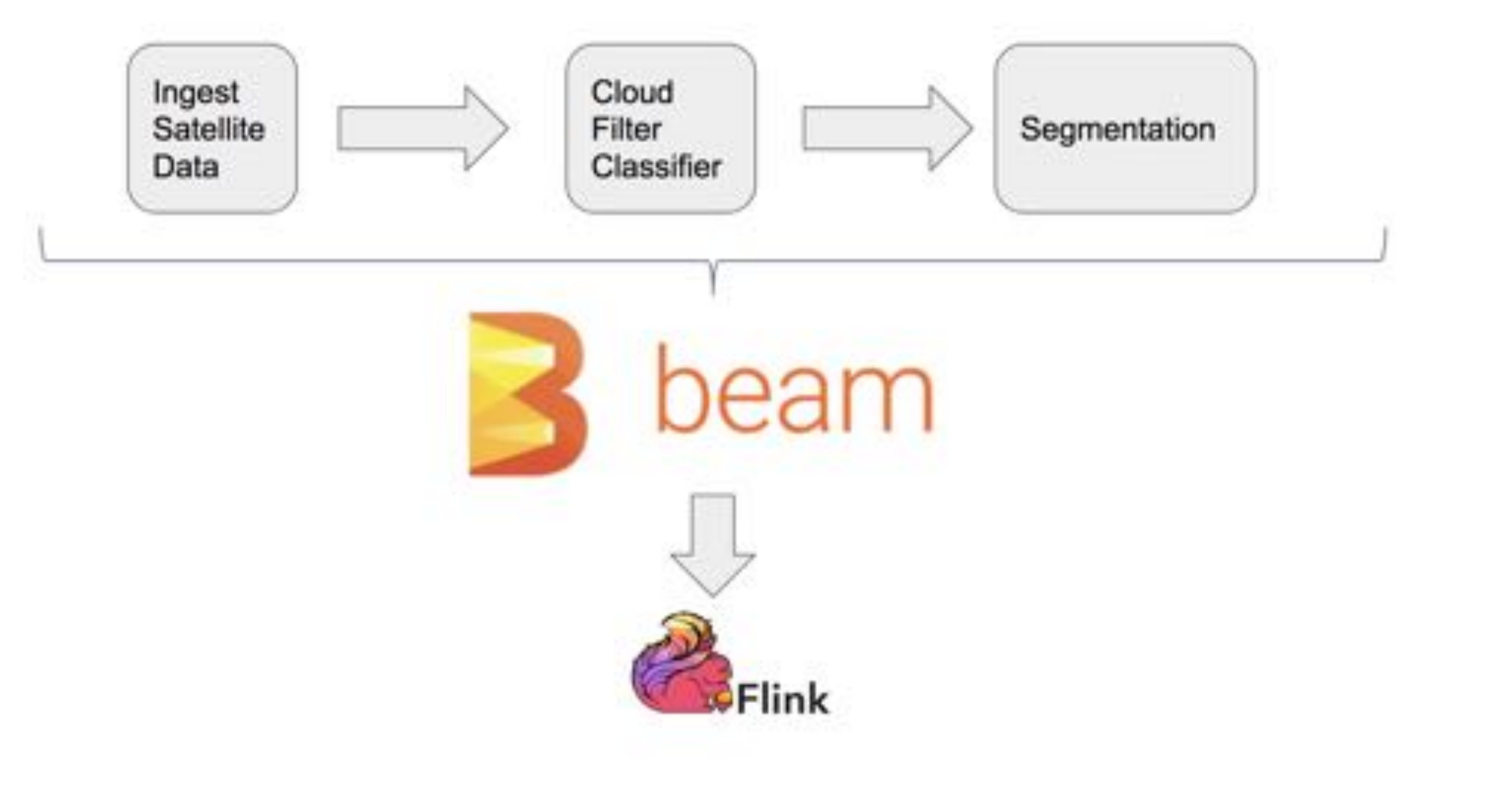
- Portierbar: Code abstraction that can be executed on different backend runners
- Vereinheitlicht: Unified batch and Streaming API
- Erweiterbare Modelle und SDK: Extensible API to define custom sinks and sources

Die Apache Beam Vision

- End Users: Create pipelines in a familiar language
- SDK Writers: Make Beam concepts available in new languages
- Runner Writers: Support Beam pipelines in distributed processing environments



Inference Pipeline



Beam Inference Pipeline

```
pipeline_options = PipelineOptions(pipeline_args)
pipeline_options.view_as(SetupOptions).save_main_session = True
pipeline_options.view_as(StandardOptions).streaming = True

with beam.Pipeline(options=pipeline_options) as p:
    filtered_images = (p | "Read Images" >> beam.Create(glob.glob
    | "Batch elements" >> beam.BatchElements(0, known_args.batchs
    | "Filter Cloudy images" >> beam.ParDo(FilterCloudyFn.FilterC

filtered_images | "Segment for Land use" >>
            beam.ParDo(UNetInference.UNetInferenceFn(known_args.m
```

Cloud Classifier DoFn

```
class FilterCloudyFn(apache_beam.DoFn):

def process(self, element):
"""
Returns clear images after filtering the cloudy ones
:param element:
:return:
"""
clear_images = []
batch = self.load_batch(element)
batch = batch.as_in_context(self.ctx)
preds = mx.nd.argmax(self.net(batch), axis=1)
idxs = np.arange(len(element))[preds.asnumpy() == 0]
clear_images.extend([element[i] for i in idxs])
yield clear_images
```

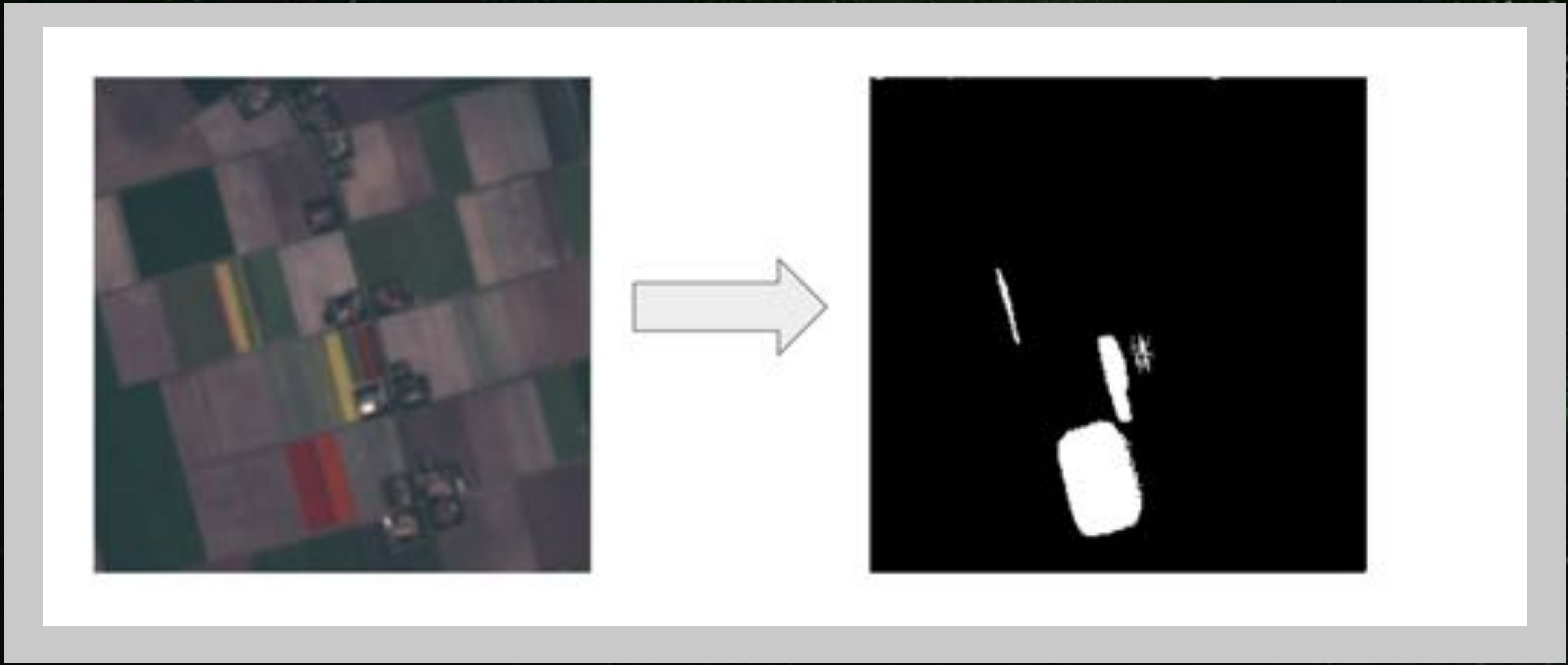
U-Net Segmentation DoFn

```
class UNetInferenceFn(apache_beam.DoFn):

    def save_batch(self, filenames, predictions):
        for idx, fn in enumerate(filenames):
            base, ext = os.path.splitext(os.path.basename(fn))
            mask_name = base + "_predicted_mask" + ext
            imsave(os.path.join(self.output, mask_name) , predict
```

Demo

No Tulip Fields

Large Tulip Fields



Small Tulips Fields

Future Work

Classify Rock Formations

Using Shortwave Infrared images (2.107 - 2.294 nm)

Radiant Energy reflected/transmitted per unit time (Radiant Flux)

$$\Phi_e = \frac{\partial Q_e}{\partial t}$$

Eg: Plants don't grow on rocks

https://en.wikipedia.org/wiki/Radiant_flux

Measure Crop Health

Using Near-Infrared (NIR) radiation

Emitted by plant Chlorophyll and Mesophyll

Chlorophyll content differs between plants and plant stages

Good measure to identify different plants and their health

https://en.wikipedia.org/wiki/Near-infrared_spectroscopy#Agriculture

Use images from Red band

Identify borders, regions without much details with naked eye - Wonder Why?

Images are in Redband

Unsupervised Learning - Clustering

Credits

- Jose Contreras, Matthieu Guillaumin, Kellen Sunderland (Amazon - Berlin)
- Ali Abbas (HERE - Frankfurt)
- Apache Beam: Pablo Estrada, Lukasz Cwik, Sergei Sokolenko (Google)
- Pascal Hahn, Jed Sundvall (Amazon - Germany)
- Apache OpenNLP: Bruno Kinoshita, Joern Kottmann
- Stevo Slavic (SAP - Munich)

Links

- Earth on AWS: https://aws.amazon.com/earth/
- Semantic Segmentation - U-Net: https://medium.com/@keremturgutlu/semantic-segmentation-u-net-part-1-d8d6f6005066
- ResNet: https://arxiv.org/pdf/1512.03385.pdf
- U-Net: https://arxiv.org/pdf/1505.04597.pdf

Links (contd)

- Apache Beam: https://beam.apache.org
- Slides: https://smarthi.github.io/BBuzz18-Satellite-image-classification-for-landuse
- Code: https://github.com/smarthi/satellite-images

Fragen ???